Fostering Scientific Reasoning Skills through Interactive Learning Tasks

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Abstract: Scientific reasoning is a key skill in academic contexts and may be trained with interactive learning tasks, that require learners to explicitly give reasons for their solution. We provide a general, mathematically motivated algebraic model for reasoning tasks that enables computer-based analysis of answers and feedback generation, especially in the case of tasks that have distinct permissible correct solutions; furthermore we present our ready sample implementation guided by that model.

1 INTRODUCTION

Scientific reasoning has been known to be an important skill for university students in order to obtain higher academic degrees, such as master's and PhD degrees. In 1933 *The American Physics Teacher* featured an article that links better ability to solve tests that involve reasoning to higher achieved academic degrees (Worthing, 1933).

Zimmerman considers the study of the development of conceptual knowledge in particular scientific domains along with the study of the reasoning and problem solving strategies involved in hypothesis generation, experimental design, and evidence evaluation to be the two main approaches to the study of scientific thinking and finds that these two approaches distinguish different connotations of scientific reasoning (Zimmerman, 2000). Domain-specific scientific reasoning typically requires the use of conceptual knowledge of a particular scientific phenomenon (Zimmerman, 2000). It has been studied among others in the domain of physics, where individuals had to use their conceptual understanding to generate solutions to tasks, but were not required to make observations, evaluate evidence, or conduct experiments (Zimmerman, 2000).

Ziegler (1990) studied solution rates for the Wason selection task (1968) for abstract implications and found an improvement of correct solution rates after training measures (Meiser and Klauer, 2001). Klauer et al. (1997) researched interference effects regarding propositional reasoning and found a significant effect of training on the number of correct solutions (Meiser and Klauer, 2001). Klauer et al. (2000) compared the effects of different training conditions on propositional reasoning: both abstract semantic training and domain-specific semantic training were significantly more effective than both syntactic and no training, whereas there were no significant differences between abstract and domain-specific training (Klauer et al., 2000).

A study conducted by Cheng et al. (1986) suggests that human reasoning relies rather on available inference schemes than on content-independent syntactic rules (Meiser and Klauer, 2001). Klaczynski et al. (1989) showed that better solution skills in one domain may be transferred to other domains if the training measures led to the acquisition of new mental representations of the logical connectives, which may be achieved by either abstract training or content-oriented training where participants are confronted with contradictions between their previous representation and the formal correct meaning of the premises (Meiser and Klauer, 2001). Content-oriented training measures that do not challenge previous representations showed no transfer effects (Meiser and Klauer, 2001; Klaczynski et al., 1989). Therefore it is important to challenge errors and misconceptions in order to train scientific reasoning skills. This may be achieved by training measures that give interactive feedback that points out possible contradictions between the mental representations of the logical connectives and their formal correct meaning. Suitable training measures may combine answer-until-correct or multiple-try feedback strategies with knowledge of performance feedback, knowledge of result feedback and elaborated feedback, such as knowledge of the location and count of mistakes (Narciss, 2008).

1.1 Interactive Learning Tasks

An interactive learning task consists of two main parts: the question or problem to be solved and its solution (Proske et al., 2012). Such a task is designed such that the series of cognitive operations and actions conducing to its outcome lead learners to be actively engaged in knowledge construction, and such that the learner may interact with a system or a person during the execution of the task in a way that supports in performing the necessary cognitive operations and actions (Proske et al., 2012). Working on interactive learning tasks may help in overcoming obstacles or in correcting incorrect solution steps, thus interactive learning tasks provide mastery experiences and foster learners' motivation (Proske et al., 2012).

Design Requirements

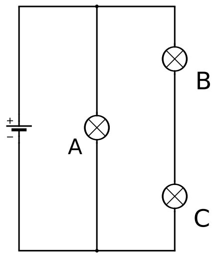
In general, interactive learning tasks should give students opportunities for repetition and correction, tutor learning task processing, and reciprocally react on learners' actions by providing feedback or other means (Proske et al., 2012). Furthermore "instructions should enable students to apply basic scientific principles flexibly, to explain or predict diverse phenomena, and to become good problem solvers and independent learners." (Reif and Scott, 1999)

In order to train scientific reasoning skills with an interactive learning task, the task must involve scientific reasoning and provide a possibility for the learner to see at which points their own reasoning is not correct in the sense of proper scientific reasoning. Thus interactive learning tasks should provide interactive feedback that not only gives information whether the solution is correct or incorrect, but also which parts of the solution contain mistakes. This should be done by providing multiple response steps with elaborated feedback components that guide the learner toward successful task completion without offering the correct response immediately (Narciss, 2008). This feedback may be given either by automated solutions or by human tutors.

1.2 Example Learning Task

We want to give an example of a learning task that involves scientific reasoning in the domain of physics.

Problem P:

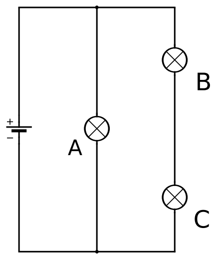


Consider the schematic to the left!
How do the luminosities of the bulbs A, B, and C relate to each other, if all three bulbs are of the same kind?

Solution. Bulb A has higher luminosity than the other bulbs and the luminosities of bulb B and bulb C are equal.

In order to give the correct solution, a student unfamiliar with such problems has to extract information from the schematic, that the bulbs B and C are connected in series and that the bulb A is connected in parallel with the bulb chain BC. Afterwards the student has to use conceptual knowledge regarding both kinds of connections in order to infer the luminosity qualities of the bulbs. On the other hand, a student familiar with such problems may be able to give the solution right away. Thus the problem has to be modified in order to train scientific reasoning:

Problem Q:



Consider the schematic to the left!
How do the luminosities of the bulbs A, B, and C relate to each other, if all three bulbs are of the same kind?
Give reasons for your answer!

Although the modified problem is well defined, it is quite cumbersome to give the solution beforehand, because there are lots of different rationales that infer the solution from the problem all of which are correct. Thus a supervisor has to undertake the tiresome and arduous task of checking each student's answer for factual correctness and completeness by following the given reasoning steps and checking their soundness.

1.3 Computer based Interactive Learning Tasks

Reif and Scott (1999) give an example computer based PAL[1] tutorial for Newton's law and its applications regarding basic Newtonian mechanics. Their computer based system offers three modes of operation: the student may be coached in implementing

[1]Personal Assistant for Learning

specified actions, the student may assess and correct the work of the PAL, and the student is provided with independent practice on similar problems (Reif and Scott, 1999). All problems of the computer based PAL tutorial example by Reif and Scott (1999) involve the creation of a diagram of all forces relevant to the mechanical system as the key step towards the solution. Although there is some non-linearity in the construction process, there is only a single valid diagram of the relevant forces per problem, which makes it easy to decide whether there are components missing and whether there are misplaced arrows or errors in the calculations – it suffices to compare the student's work against the correct solution of the problem, and to give feedback accordingly.

1.4 Reasoning in Learning Tasks

Learning tasks that require the student to explicitly do scientific reasoning as part of the solution have more than only one distinct correct answer in general: Consider problem Q. We might argue that the same voltage means the same luminosity. But we also might argue that the same current means the same luminosity. If we chose the first argument, we could say that the current through bulb B is the same as the current through bulb C, thus bulb B and bulb C are equal bright. If we chose the second argument, we would argue that the voltage of bulb B is as big as the voltage of bulb C, thus they have the same luminosity. In order to systematically give interactive feedback for learning tasks that require scientific reasoning, we need a model of reasoning. Although a complete model of scientific reasoning could be used as well, incomplete – and sometimes much easier – models that only cover those aspects of scientific reasoning that are relevant to give interactive support and to check the student's answer will suffice.

2 ALGEBRAIC MODEL OF REASONING IN INTERACTIVE LEARNING TASKS

In this section, we will provide an algebraic background model that is sufficient to generate appropriate interactive learner's feedback for scientific reasoning tasks.

The atomar entity of reasoning that we are dealing with is an assertion, and the *set of all assertions* will be denoted by A. Furthermore we will denote the two-elementary complete lattice by

$$\mathbb{L} = (L, \leq, \bigvee, \bigwedge, 0, 1)$$

and interpret 0 as false or incorrect, and 1 as true or correct.

Each implementation of an interactive learning task has a set of assertions that a learner may use in order to generate her answer. This set is called *assertion domain* and will be denoted by $D' \subseteq A$. For obvious reasons any assertion $a \in D'$ must be of a form such that it is either is true or false within the context of the learning task, thus there is a map $v\colon D \to L$ that maps each decidable assertion $a \in D \subseteq A$ to its truth value $va \in L$, and $D' \subseteq D$.

2.1 Stating Reasons as Inverse Inference

If we ask for reasons for a specific assertion we would be satisfied if we got some assertions from which we could somehow infer the former assertion. This circumstance may be captured by the following: We let n be a natural number, then we will call any $n+1$-ary relation on D an *inference rule*, i.e. I is an inference rule if $I \subseteq D^{n+1}$ for some natural number n that depends on I. We will interpret

$$(a_1, a_2, \ldots, a_n, a_{n+1}) \in I$$

such that the assertions a_1 through a_n are considered to be reasons for a_{n+1} w.r.t. I.

Of special interest are *valid inference rules*: An inference rule $I \subseteq D^{n+1}$ is called valid, if for all $a_1, a_2, \ldots, a_n, a_{n+1} \in D$

$$\bigwedge_{i=1}^{n} va_n \leq va_{n+1}$$

holds. If we have a given set of valid inference rules, we can use it to generate new correct assertions from known-to-be-correct assertions, and to verify that some given reasons are indeed sufficient for some assertions.

2.2 Using Inference Bases to Decide Correctness in D'

If we want to check whether an assertion $a \in D'$ is correct, we can use an initial set of correct assertions $A_0 \subseteq D$ and a set of valid inference rules R. We will successively extend our knowledge of correct assertions: starting with A_0 we apply all the rules $I \in R$ to all combinations of correct assertions we know and continue with combinations involving assertions we just gained knowledge of until no more new correct assertions arise. Thus we are closing A_0 under R:

$$\begin{aligned} \overline{A_0}^R = \bigcap \quad & \{A \in 2^D \mid A_0 \subseteq A, \\ & \forall I \in R, a_1, \ldots, a_n \in A, \\ & a_{n+1} \in D\colon \\ & (a_1, \ldots, a_n, a_{n+1}) \in I \Rightarrow a_{n+1} \in A\} \end{aligned}$$

Although we can use any such pair (A_0, R) to verify that an assertion $a \in D'$ is indeed correct, we need another property of (A_0, R) in order to know that an incorrect assertion a is indeed incorrect: We consider a pair (A_0, R) – where $A_0 \subseteq D$ and R is a set of inference rules – to be a D'-*base*, if for all $a \in D'$

$$va = 1 \Leftrightarrow a \in \overline{A_0}^R$$

This means that if we have a given D'-base we may close its set of correct assertions under its set of inference rules and use the resulting set of correct assertions to check whether an assertion $a \in D'$ from the assertion domain of the interactive learning task implementation is correct within this context. If the assertion is in the closure, i.e. $a \in \overline{A_0}^R$, it is correct, otherwise it is incorrect. An author creating an implementation of such a task now only has to give a sufficient amount of both valid inference rules and correct assertions[2] in contrast to having to enter all correct assertions from D'.

2.3 Checking Reasons for Assertions

We also want to use valid inference rules to check whether a given argumentation – which we consider to be merely a set of assertions $P \subseteq D'$ – contains reasons for all of the non-trivial and non-obvious correct assertions that it contains. Therefore we want to use a set R of inference rules, where every inference rule $I \in R$ represents a satisfactory way of arguing.[3]

Let (A_0, R) be a D'-base where every $I \in R$ also represents a way of arguing, and let $P \subseteq D'$ be a given argumentation. We further assume that $P \subseteq \overline{A_0}^R$, i.e. that all assertions from P are correct. In order to check whether the argumentation P is not missing any reasons from the assertion domain D', we will start with the trivial and obvious assertions from P, and then try to use rules $I \in R$ to successively justify new assertions from P. Thus we compute the relative closure of the empty set $\emptyset$ with regard to P under R:

$$\begin{aligned} \widetilde{P}^R \quad = \bigcap \quad & \{A \in 2^P \mid \forall I \in R, \\ & a_1, \ldots, a_n \in P \cup (\overline{A_0}^R \backslash D'), \\ & a_{n+1} \in P: \\ & (a_1, \ldots, a_n, a_{n+1}) \in I \Rightarrow a_{n+1} \in A\} \end{aligned}$$

Clearly, the set $\widetilde{P}^R$ consists of those assertions from the argumentation P that are either trivial or obvious, or that may be satisfactory justified by other given assertions. In other words, the set $P \backslash \widetilde{P}^R$ contains the assertions from P for which the student should give more reasons.

[2]Those assertions do not necessarily have to be from the assertion domain the student is composing her answer from.

[3]Note that 1-ary inference rules $I \subseteq D^1$ represent obvious or trivial assertions, since they are contained in the closure of the empty set $\overline{\emptyset}^R$.

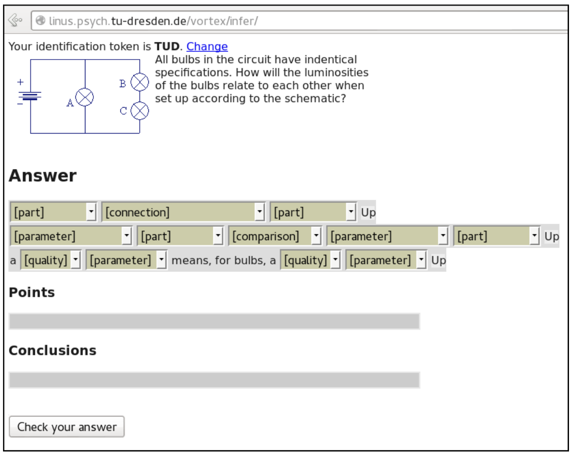


Figure 1: Screenshot of a sample implementation of problem Q.

3 IMPLEMENTING AN INTERACTIVE LEARNING TASK ON SCIENTIFIC REASONING

In order to demonstrate that our algebraic modeling approach is fruitful we have developed and implemented an interactive learning platform that works in a standard Java and JavaScript enabled web-browser. Below we will sketch how an interactive learning platform web page as seen in figure 1 can be created for problem Q. The interactive learning web page contains a description of the problem, along with a template kit that can be used to construct sentences, which subsequently can be dragged into separate areas, one for the answer of the question and one for reasons that lead to the answer. After entering the answers and reasons the student can request the web site to check the answer, in which case the student is provided with information whether each point is correct, whether the student should give more reasons for each point, and whether there are points regarding the schematic or the underlying physical laws missing.

3.1 Working with the Algebraic Model of Reasoning

First, we need to choose a good assertion domain D' for the learning task. Any number of sentences

Table 1: Sentence template for the description of the schematic.

bulb A	is serial connected with	bulb A
bulb B	is connected in parallel with	bulb B
bulb C		bulb C
bulb chain BC		bulb chain BC
the battery		the battery

Table 2: Sentence template for the comparison of circuit element parameters.

the current through	bulb A	is smaller than	the current through	bulb A
the voltage of	bulb B	is as big as	the voltage of	bulb B
the resistance of	bulb C	is bigger than	the resistance of	bulb C
the input power of	bulb chain BC		the input power of	bulb chain BC
the luminosity of	the battery		the luminosity of	the battery

Table 3: Sentence template for the relations between the parameters.

a	smaller	current	means, for bulbs, a	smaller	current
	bigger	voltage		bigger	voltage
		resistance			resistance
		input power			input power
		luminosity			luminosity

Table 4: Examples for the inference rule set of our implementation of problem Q.

rule name	*example reasons*	*example conclusion*
schematic to comparison	bulb B is serial connected with bulb C	the current through bulb B is as big as the current through bulb C
comparison transitivity	the voltage of bulb A is as big as the voltage of bulb chain BC the voltage of bulb chain BC is bigger than the voltage of bulb B	the voltage of bulb A is bigger than the voltage of bulb B
parameters & comparison	the voltage of bulb A is bigger than the voltage of bulb B a bigger voltage means, for bulbs, a bigger luminosity	the luminosity of bulb A is bigger than the luminosity of bulb B
comparison inversion	the voltage of bulb A is bigger than the voltage of bulb B	the voltage of bulb B is smaller than the voltage of bulb A
parameter transitivity	a bigger current means, for bulbs, a bigger voltage a bigger voltage means, for bulbs, a bigger luminosity	a bigger current means, for bulbs, a bigger luminosity
parameter inversion	a bigger current means, for bulbs, a bigger voltage	a bigger current means, for bulbs, a bigger voltage
quantifier negation	a bigger voltage means, for bulbs, a bigger luminosity	a smaller voltage means, for bulbs, a smaller luminosity
schematic inversion	bulb B is serial connected with bulb C	bulb C is serial connected with bulb B
schematic transitivity	the battery is connected in parallel with bulb A bulb A is connected in parallel with bulb chain BC	the battery is connected in parallel with bulb chain BC

from this domain may be chosen by the student and dragged into the *points* or *conclusions* areas of the web page. We would like to point out that the choice of a good assertion domain D' is the key step in our endeavor of creating a good interactive learning task implementation for a given problem. Serious effort and consideration should be put into this step before doing any of the technical steps, since changes regarding the assertion domain usually effect all subsequent work. Clearly, the student has to describe the components of the schematic. In order to do this, the student may compose sentences by choosing an option from each of the columns given in table 1. The student also has to compare some of the electrical and physical parameters of the circuit elements by constructing sentences from options given in table 2. And last the student has to give information on how the parameters will influence each other regarding the bulbs. This can

Table 5: Initial set of correct assertions for our implementation of problem Q.

bulb A is connected in parallel with bulb chain BC
the battery is connected in parallel with bulb A
bulb B is serial connected with bulb C
the resistance of bulb A is as big as the resistance of bulb B
the resistance of bulb A is as big as the resistance of bulb C
the resistance of bulb chain BC is bigger than the resistance of bulb C
the voltage of bulb chain BC is bigger than the voltage of bulb B
a bigger voltage means, for bulbs, a bigger current
a bigger voltage means, for bulbs, a bigger input power
a bigger input power means, for bulbs, a bigger luminosity

be done by composing sentences from table 3. These three sentence templates constitute the assertion domain D', which has 2025 elements – sentences[4] which the student may use to complete the task.

After we have chosen the assertion domain for our implementation we have to think about the relations between the assertions and come up with an appropriate set R of valid inference rules. Since giving all the inference rules $I \in R$ in detail is a technical and tiresome task that does not provide deeper insights, we will only sketch the inference rules of our implementation here by sparing the technicalities and giving an example for each rule in table 4 instead.

Further we consider all correct assertions regarding the schematic, the fact that the voltage of the bulb chain BC is bigger than the voltage of each of the bulbs B and C, and the relations between the parameters to be obvious for our problem and hence do not demand reasons for them.

Having fixed the assertion domain D' and the set of inference rules R we need to give a set of assertions $A_0 \subseteq D$ such that (A_0, R) is a D'-base. In table 5 we list a set of assertions sufficient to determine whether any assertion $a \in D'$ from the assertion domain is correct.

4 CONCLUSIONS AND FURTHER WORK

In this paper we showed that scientific reasoning is an important skill that can be trained by appropriately designed interactive learning tasks. We elaborated a profound model that can be used to generate interactive web-based learning platforms that may provide feedback and tutor learners in order to improve their reasoning skills across different tasks and domains. We presented a sample implementation using a general framework. As part of future work this implementation framework may be used to create further computer-based interactive learning tasks, on which highly needed further empirical studies on training scientific reasoning may be based.

[4]Notice that there are different sentences that essentially carry the same information, but since we allow for distinct solutions anyway, there is no need to enforce a normalized way of generating sentences from underlying information.

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